Application of Robust-IC Intelligent Control System for Plant-Wide Production Processes in Ethylene Plant

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Abstract: Due to the long duration and complicatedness, the ethylene production process has problems of modeling and control such as multivariable, nonlinear, strong coupling, pure lag, intermittent and continuous control coexistence, multi-constraint and multi-target regulation. To solve these problems, intelligent modeling, intelligent internal model set control, intelligent internal model set control technology intelligent adjustable parameter nonlinear control technology, beacon fire control technology were developed. Based on the above technologies, the Robust-IC intelligent control system for plant-wide production processes was formed in this paper. Using the control system, the sum of ethylene propylene yield in the naphtha furnace and the ethane furnace was increased by 0.52% and 1.99%, respectively, the energy consumption was reduced by 40.12 kg of standard oil per ton of ethylene and the cumulative economic benefits of three years is USD $ 127 million.

Keywords: dynamic modeling; intelligent control; multivariable; nonlinear; beacon fire control

1. Introduction

As we know, the process of ethylene production has the characteristics of long duration, multi variation, strong coupling, nonlinearity, and large time lag, and the separation system has many problems such as multi-objective, multi-constraint, self-interference, and front-back coupling [1]. In the recent years control technology has always been the focus of research at home and abroad. The ethylene industry adopts a reliable DCS (Distributed Control System) distributed control system. More than 95% of its control loops still use PID (Proportion Integration Differentiation) control [2,3]. The PID control has a low self-control rate and does not fully utilize the advantages of DCS, which cannot meet the requirements of the petrochemical industry. In order to improve the safe operation level of ethylene production equipment, technologies and products such as intelligent modeling, intelligent internal model set control, intelligent adjustable parameter nonlinear control, multivariable intelligent control, beacon fire control were developed [4,5]. Based on the above technologies, the Robust-IC intelligent control system for plant-wide production processes was formed [6,7]. The system is applied in the ethylene plant to realize adaptive, self-learning, safe and reliable intelligent control of the ethylene production.

2. Robust-IC Intelligent Control System for Plant-Wide Prodtion Processes

The Robust-IC intelligent control system for plant-wide production processes fully exploits the potential of existing processes and equipment without changing the existing process and equipment conditions, and utilizes the advantages of information technology to keep the production equipment in an optimal state. The core technical contents are as follows.

2.1. Intelligent Modeling Technology

Based on data access technology, automatic acquisition of big data in production process. Use industrial big data mining methods to obtain effective process data. The effective data is preprocessed by lifting wavelet analysis technology. It integrates elite strategy, orthogonal analysis, NLJ algorithm, self-learning, self-correction theory and method, and establishes a continuous transfer function dynamic model of process object in a short time. Process object transfer function model as Eq. (1).

$$G_M(s) = \frac{b_0 s^{n_b} + b_1 s^{n_{b-1}} + \ldots + b_{n_b}}{s^{n_a} + a_1 s^{n_a - 1} + \ldots + a_{n_a}} e^{-\tau s} \qquad (1)$$

In the Eq. (1), $a_1, a_2 \ldots a_{n_a}$ and $b_0, b_1 \ldots b_{n_b}$ means model parameters, s means Laplace operator, n_a and n_b represent the order of the denominator and the molecule, respectively, and $n_a > n_b$. τ express pure lag time. As the production data increases, a model library covering all working conditions is automatically generated. The multivariate model library as Eq. (2).

$$G=\begin{bmatrix} G_{11}(s) & G_{12}(s) & \cdots & G_{1n}(s) \\ G_{21}(s) & G_{22}(s) & \cdots & G_{2n}(s) \\ \vdots & \vdots & \cdots & \vdots \\ G_{m1}(s) & G_{m2}(s) & \cdots & G_{mn}(s) \end{bmatrix} \quad (2)$$

In the Eq. (2), m represents the number of model libraries, n represents the number of models included in each model library. The ISE criterion was used to establish an accuracy evaluation standard for object identification models, and the model accuracy was over 95%, achieving high-precision intelligent modeling.

2.2. Intelligent Internal Model Set Control Technology

The intelligent internal model set control technology improves the controller design method. The model control technology is used to intelligently select the working condition model set from the model library. The controller parameters of the design model set are seamlessly embedded in the PID controller through data access technology. The traditional PID control is upgraded to intelligent control, forming the Robust IMSC intelligent internal model set controller. It does not change the original PID structure and operating habits, is maintenance-free, and can be widely applied.
The relationship between intelligent control, internal model control and model as Eq. (3).

$$G_{IMSC}(s)=\frac{G_{IMC}(s)}{1-\tilde{G}_M(s)G_{IMC}(s)} \quad (3)$$

In this Eq. (3), $G_{IMSC}(s)$ represents the intelligent controller. $G_{IMC}(s)$ represents the internal model controller, and $\tilde{G}_M(s)$ represents intelligent model in intelligent model library. The intelligent internal model set control principle and structure diagram is shown as Figure 1 below.

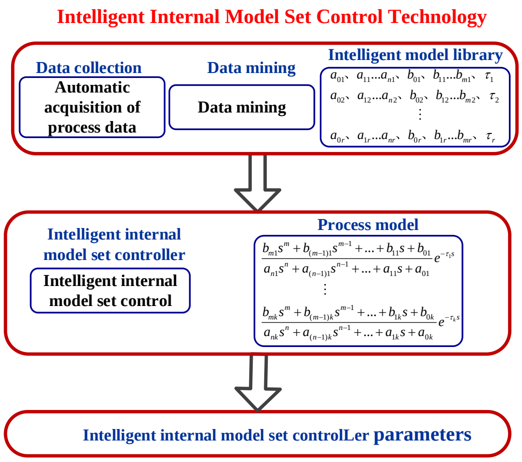


Figure 1. Intelligent internal model set control principle and structure diagram

2.3. Intelligent Adjustable Parameter Nonlinear Control Technology

The ethylene production process is long and the processes are closely related. With the large scale of the production equipment, the technical difficulties of upstream and downstream interference are highlighted. By adopting intelligent modeling, fuzzy control and expert system, an intelligent adjustable parameter nonlinear control technology is proposed. According to the influence of interference, the main control parameters are nonlinearly changed, and the sub-control parameters are smoothly controlled. The design method is as Eq. 4) and Eq. (5).

$$\begin{cases} K_e=\alpha\cdot\dfrac{|E(t)|}{2TW}\cdot K_p+\dfrac{1}{2}\alpha\cdot K_p, & |E(t)|\le TW \\ K_e=\alpha\cdot e^{(\frac{|E(t)|}{TW}-1)}\cdot K_p\ , & TW<|E(t)|\le TW\cdot\ln(\dfrac{\beta e}{\alpha}) \\ K_e=\beta K_p\ , & |E(t)|>TW\cdot\ln(\dfrac{\beta e}{\alpha}) \end{cases} \quad (4)$$

$$\begin{cases} I_e=\dfrac{B-\frac{\beta}{\alpha}}{TW}\cdot I_p\cdot E(t)+\dfrac{\beta}{\alpha}\cdot I_p\ , & |E(t)|\le TW \\ I_e=\dfrac{1-B}{A\cdot TW}\cdot I_p\cdot E(t)+\dfrac{A\cdot B+B-1}{A}\cdot I_p\ , & TW<|E(t)|\le TW\cdot\ln(\dfrac{\beta e}{\alpha}) \\ I_e=I_p\ , & |E(t)|>TW\cdot\ln(\dfrac{\beta e}{\alpha}) \end{cases} \quad (5)$$

In this Eq. (4) and Eq. (5), K_p represents the scale factor, K_e represents the actual scale factor, $E(t)$ represents the parameter after the fuzzy output is defuzzied, TW represents the set threshold. α and β represent variable coefficient. I_p represent integral constant, I_e represent the actual integral constant. $A=\ln(\dfrac{\beta}{\alpha})$ and $B=\dfrac{2A\cdot\frac{\beta}{\alpha}+1}{2A+1}$ are constant.

For the multi-parameter control loop, the intelligent adjustable parameter nonlinear control technology is adopted to realize the regional control, that is, the non-key indicators can fluctuate within the set range, the key indicators are stable, and the self-interference between the internal parameters after the large-scale device scale is reduced. After the application of the technology, the lifting device is resistant to disturbance and ensures stable operation of the system.

2.4. Multivariable Intelligent Control Technology

There are many devices in the ethylene production process, the number of parameters is large, and the correlation between parameters is deep. The overall control is difficult, and the traditional control method is difficult to solve. Aiming at the control characteristics and difficulties of multi-parameter groups, multivariable intelligent control technology method was developed to run big data based on production. The sub-model and sub-sub model modeling methods are used to establish multi-case and multi-level multivariate models, and multi-constrained controllers with multiple constraints, multi-objectives and high dimensions are designed to coordinate multi-level control objectives and hierarchical management. The multivariate parameter group control process realizes multi-level, high-dimensional, multi-objective multi-variable intelligent control. After the implementation of the technology, the safety of the production process is ensured, the labor intensity of the operator is reduced, the production process is directly implemented, the control precision is high, and the utility model can be stably used for a long time, and is suitable for various working conditions such as opening and stopping.

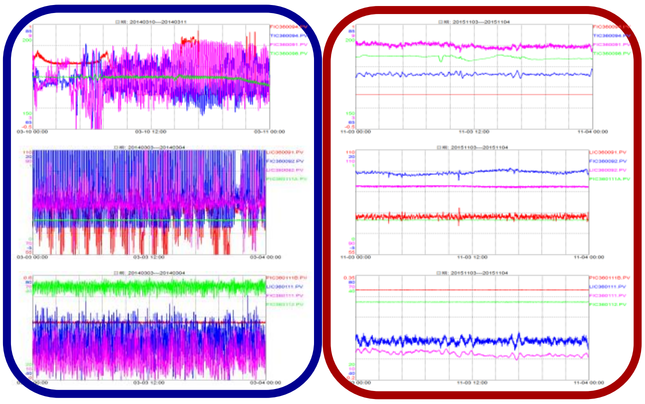
2.5. Beacon Fire Control Technology

In order to adapt to the market demand, it is necessary to switch the production plan, the transition time is long, the parameters fluctuate greatly, the operation is difficult, and the safety and smooth operation are affected. Aiming at the problem of switching process disturbance, beacon fire Control method is proposed. Beacon fire control method is based on the dynamic and static balance of materials and energy before and after the production plan, intelligently assign relevant process parameters, and automatically adjust the relevant process parameters step by step. The whole switching process realizes one-button intelligent operation, which simplifies the operation process, eliminates the interference between related processes, reduces the fluctuation caused by the change of production plan, and solves the running problem of the switching process.

3. Application of Robust-IC Intelligent Control System for Plant-Wide Production Processes In 600 kt/a ethylene plant of PetroChina Daqing Petrochemical

Intelligent modeling technology has been operating in 600 kt/a ethylene plant of PetroChina Daqing Petrochemical for nearly 4 years. A total of tens of billions of production process data were collected, and a total of 652 object model libraries were established. Each model library contained an average of 960 models, totaling 625,920 models, and the model accuracy was 98%.

After the application of the intelligent internal model set control technology in Daqing Petrochemical ethylene plant, the automatic control of investment rate is increased from 80% to 99%, the smooth investment rate is 100%, the control precision is improved, and the operation is stable. The control effect is presented in Figure 2 blow.



Before control After control

Figure 2. Daqing Petrochemical debutanizer control effect diagram

Multivariable intelligent control was applied in in Daqing petrochemical ethylene plant cracking furnace, and 7 cracker multivariate model libraries were established. Each multivariate model library contains 504 full working conditions models with self-learning and self-adaptation. Capability, model accuracy of 98%. According to the importance of the control variables such as cracking furnace cot, branch temperature, feed, dilution steam, etc., all variables are confirmed in real time. If the variable is within the constraint range, it is normally adjusted, beyond the constraint range, and the layers are coordinated according to the priority, and the step-by-step adjustment is automatically performed. Based on the heat balance theory, the heat value and load control are introduced to improve the hysteresis problem of fuel gas composition and load change, and finally realize the smooth operation of the cracking furnace. After implementation, the fluctuation range of cot decreased to ±0.73 ℃, the mean square error decreased to 0.43 ℃, the diene yield of naphtha furnace increased by 0.52%, and the ethane furnace increased by 1.99%.

The beacon fire control is applied in the cracking furnace of the ethylene plant, realizing the automatic lifting and lowering load, the cot temperature of the cracking furnace, the temperature difference of the branch road, the feeding of the branch road, and the smooth control of the dilution steam, effectively ensuring the stable operation of the whole device. The cracking furnace automatic lifting load effect is shown in Figure 3 below.

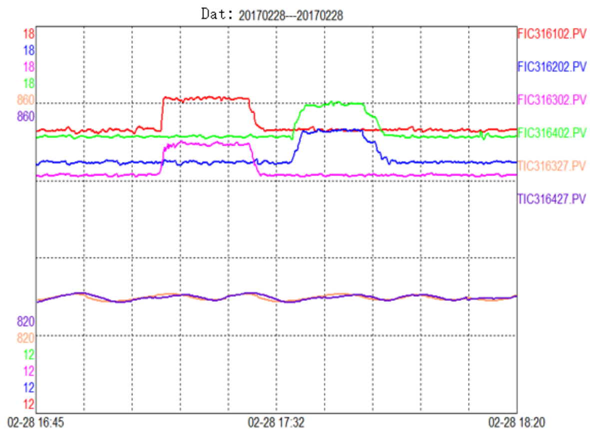


Figure 3. Cracking furnace automatic lifting load effect diagram

4. Process Model Set Identification

The identification of process model set is based on process valid data set. After generating the valid data set of process model identification, the process model set under different working conditions is established by using Random Orthogonal Algorithms (ROAS) and Integral of Square Error (ISE) index with the obtained model parameters as initial values. The process model is the second-order pure delay model shown in the following formula.

$$P_i(s) = \frac{c_i s + d_i}{a_i s^2 + b_i s + 1} e^{-\tau_i s} \tag{6}$$

where $a_i, b_i, c_i, d_i, \tau_i$ are the parameters of the process model P_i, $i = 1,2,\cdots,n$ to be identified. n is the number of models in the model set and s is the Laplace transform operator.

According to the corresponding open-loop or closed-loop mode, the ROAS algorithm is applied to identify the open-loop/closed-loop process model for each data group in the effective identification data set. Similarly, the process model set of the loop is formed by evaluating and choosing the model by identifying the confidence function.

Formula (7) is used as objective function in process model identification to identify the parameters of second-order plus pure delay transfer function.

$$ISE_i = \sum_{j=1}^{n_i} (y_j - \hat{y}_j)^2 \tag{7}$$

where y_j the output of process object is, $\hat{y}_j$ is output response of process model.

4.1. Model PID Parameter Tuning based on Process Model Set

PID parameter tuning is a set of optimal PID parameter processes based on process model set. By establishing the PID control structure of model set and taking time multiplied absolute error integral (ITAE) as performance index, all models have good control performance. The parameter tuning process can be automatically and effectively circulated without the participation of personnel. This method has been applied to the continuous operation of the production plant. The results show that the method greatly improves the robustness and anti-interference of the control loop, and ensures the safe and stable operation of the production plant.

Model PID parameter tuning based on process model set is a method to directly optimize the parameters of PID controller by using the obtained process model set and using random number search optimization algorithm (ROAS). The purpose of PID parameter tuning is to find a set of PID parameters including P (Proportioning constant), I (Integral time constant) and D (Differential time constant), so that under the control of these parameters, all the models in the controlled process have good dynamic response performance, that is, the performance index formula (8) reaches the minimum. The working schematic diagram of PID parameter tuning is shown in Figure 4.

$$ITAE = \sum_{i=1}^{n} \sum_{j=1}^{n_i} | f(r_j) - r_j | \cdot t_j \tag{8}$$

where t_j is the sampling time from 0, r_j is the set value at time t_j, $f(r_j)$ is the set value response at time t_j. n_i is the number of elements in the i th identification data set. n is the number of elements in model set.

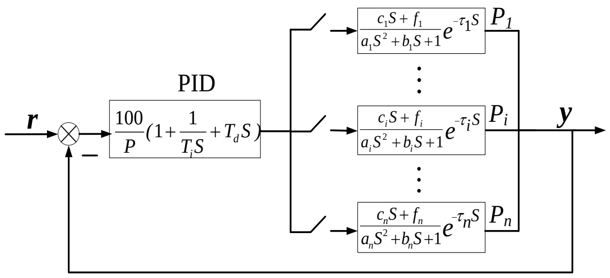


Figure 4. PID parameters tuning configuration based on set of models

The steps of PID parameter tuning based on model set are as follows:

- Taking the PID parameters of the current loop as initial values, several sets of PID parameters and initial values are randomly generated within a given search range to form a search vector group.
- For each search vector of the generated search vector group, the ROAS algorithm is used to optimize the PID parameters with formula (8) as the objective function.
- According to the original PID parameters and the optimized PID parameters, the dynamic responses of each model in the model set are calculated respectively, and the response curves are given.

4.2. Model PID Parameter Tuning based on Process Model Set

IMC-PID parameter tuning algorithm has unique advantages in the process of PID parameter tuning which can also be realized by process model set. The key to the tuning of IMC-PID parameters is to obtain the IMC controller, and then to obtain the parameters of the PID controller by using the relationship between the IMC controller and the PID controller.

A design method of IMC controller based on process model set is presented in this paper: For all process models in process model set, ROAS algorithm is applied to obtain both filter constants and internal model parameters, so that the obtained IMC controller has good control performance and robustness to all process model sets. The design structure of IMC controller based on model set is shown in Figure 5. Its aim is to find an IMC controller so that all process models $P_i\ (i=1,2,\cdots,n)$ in process model set can obtain good dynamic response performance under the control of the controller. The IMC controller in the model set IMC control system shown in Figure 5 consists of a first-order filter and an inverse part of the left half plane of the internal model IM. The internal model IM in Figure 5 has the following forms

$$G_{IM} = \frac{cS+f}{aS^2+bS+1}\mathrm{e}^{-\tau S} \tag{9}$$

The corresponding IMC controller is

$$G_{IMC} = \frac{aS^2+bS+1}{cS+f}\times\frac{1}{\lambda S+1} \tag{10}$$

where λ is filter constant, a, b, c, f and τ are internal model parameters.

The solution of IMC controller based on model set is to find a set of filter constant λ and internal model parameters a, b, c, f, τ. By applying these parameters, the IMC controller can achieve good control performance and strong robustness for all process models P_i. In Figure 5, y is measured value, r is loop settings.

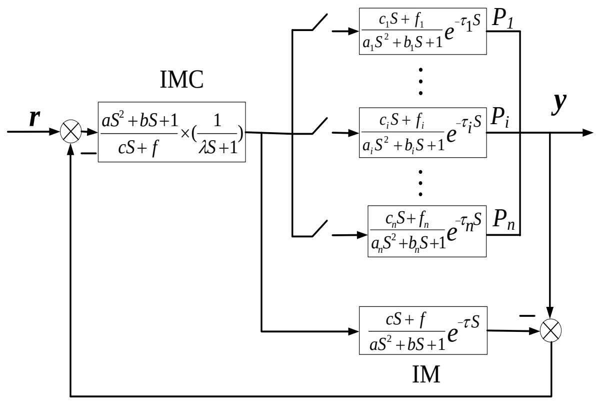


Figure 5. IMC-PID parameters tuning configuration based on set of models

Based on the design process of the model set IMC controller, ROAS optimization algorithm is used to calculate the output of the internal model and the output of the closed-loop system by giving the initial value and step input of the filter parameters and the internal model. The objective is to minimize the cost function described by formula (4-15). At the same time, the parameters of the IMC controller and the IM parameters are optimized.

In the design process of IMC controller based on model set, ROAS optimization algorithm is used to calculate the output of internal model and the output of closed-loop system by giving the initial value and step input of filter parameters and internal model. Aiming at minimizing the cost function described by formula (11), the parameters of IMC controller and IM parameters are optimized.

$$ITAE = \sum_{i=1}^{n}\sum_{j=1}^{n_i}(|\ f_i(r_j)-r_j\ |+|\ f_i(r_j)-f_i(IM)\ |)\cdot t_j \tag{11}$$

where $f_i(r_j)$ is the closed loop computational output at time t_j, r_j is the loop settings at time, $f_i(IM)$ is the output of internal model, t_j is the sampling time from 0

The steps of IMC-PID parameter tuning based on model set are as follows:

- Taking the mean values of $a_i, b_i, c_i, f_i, \tau_i$ in model set as the initial parameters of IMC controller, filter constant λ is given and a number sets of IMC parameters are randomly generated within a given search range to form a parameter vector group.
- For each search vector of the generated search vector group, the ROAS algorithm is used to optimize the PID parameters with formula (11) as the objective function.
- According to the optimization parameter calculation model, the IMC dynamic response of each model is centralized, and the response curve is given.
- According to the relationship between IMC and PID controller, the parameters of IMC-PID control are calculated.
- According to the original PID parameters and the optimized IMC-PID parameters, the dynamic responses of each model in the model set are calculated respectively, and the response curves are given.

5. Conclusion

Based on the research on the intelligent control of ethylene plant production process, on the basis of giving full play to the advantages of DCS system, we develop technologies and products such as intelligent modeling, intelligent internal model set control, intelligent variable parameter nonlinear area control, multivariable intelligent control and the beacon fire control. Based on the above technologies and products, a full-process intelligent control system is formed and applied in 600 kt/a ethylene plant of PetroChina Daqing Petrochemical. After application, the diene yield of naphtha furnace increased by 0.52%, the ethane furnace increased by 1.99%, the average ethylene energy consumption decreased by 40.12 kg standard oil per ton ethylene, and the direct economic benefit realized in the past three years is USD $ 127 million. The overall control level of the ethylene plant is greatly improved, and it can be used for a long time under various working conditions such as opening, stopping, entering, returning, and switching raw materials, fully improving the smoothness and safety of the operation of the production process, reducing the labor intensity of the operator, and reducing the probability of misuse. Extend the production cycle, extend the service life of equipment such as furnace tubes, reduce production costs, save energy and reduce emissions.

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